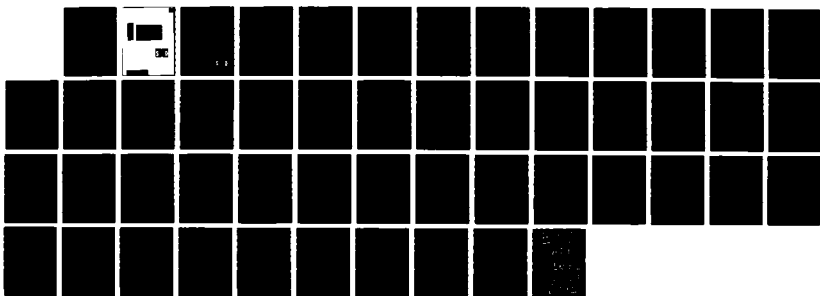


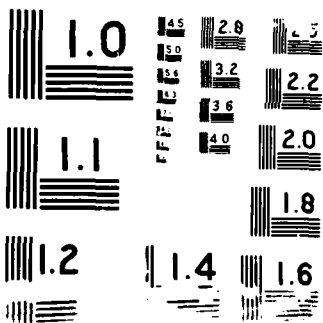
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Venture Theory: A Model of Decision Weights

Robin M. Hogarth Hillel J. Einhorn
University of Chicago
Graduate School of Business
Center for Decision Research

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Sponsored by:
Perceptual Sciences Program
Office of Naval Research
Contract Number N00014-84-C-0018
Work Unit Number NR 197-080

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SECURITY CLASSIFICATION OF THIS PAGE

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION Unclassified			1b. RESTRICTIVE MARKINGS NONE	
2a. SECURITY CLASSIFICATION AUTHORITY NA			3. DISTRIBUTION/AVAILABILITY OF REPORT Approved for public release; distribution unlimited.	
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE				
4. PERFORMING ORGANIZATION REPORT NUMBER(S) Center for Decision Research Report #21			5. MONITORING ORGANIZATION REPORT NUMBER(S)	
6a. NAME OF PERFORMING ORGANIZATION Center for Decision Research University of Chicago		6b. OFFICE SYMBOL (If applicable)	7a. NAME OF MONITORING ORGANIZATION Office of Naval Research	
6c. ADDRESS (City, State, and ZIP Code) 1101 East 58th Street Chicago, Illinois 60637			7b. ADDRESS (City, State, and ZIP Code) 800 North Quincy Arlington, Virginia 22217	
8a. NAME OF FUNDING/SPONSORING ORGANIZATION Office of Naval Research		8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER Contract #N00014-84-C-0018	
8c. ADDRESS (City, State, and ZIP Code) Perceptual Sciences Program Office of Naval Research, Code 1142PS Arlington, Virginia 22217-5000			10. SOURCE OF FUNDING NUMBERS	
			PROGRAM ELEMENT NO. 61153-N	PROJECT NO.
11. TITLE (Include Security Classification) VENTURE THEORY: A MODEL OF DECISION WEIGHTS.				
12. PERSONAL AUTHOR(S) Robin M. Hogarth and Hillel J. Einhorn				
13a. TYPE OF REPORT Technical		13b. TIME COVERED FROM _____ TO _____		14. DATE OF REPORT (Year, Month, Day) January 1988
15. PAGE COUNT 48				
16. SUPPLEMENTARY NOTATION				
17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number) Risk; ambiguity; uncertainty; decision weights.	
FIELD	GROUP	SUB-GROUP		
19. ABSTRACT (Continue on reverse if necessary and identify by block number)				
<p>Several theories suggest that people replace probabilities by decision weights when evaluating risky outcomes. This paper proposes a model, called venture theory, of how people assess decision weights. It is assumed that people first anchor on a stated probability and then adjust this by mentally simulating other possible values. The amount of mental simulation is affected both by the extent to which the anchor deviates from the extremes of 0 and 1 (i.e., where there is no uncertainty) and the level of perceived ambiguity concerning the relevant probability. The net effect of the adjustment (i.e., up or down relative to the anchor) reflects the relative weight given in imagination to values above as opposed to below the anchor. This, in turn, is taken to be a function of both individual and situational variables, and in particular, the sign and size of payoffs. Cognitive and motivational factors therefore both play important roles in determining decision weights. Assuming that people evaluate outcomes by a prospect theory value function (Kahneman & Tversky, 1979) and are cautious in the face of risk, predictions are derived concerning attitudes toward risk and ambiguity as functions of different levels of payoffs and probabilities. The results of two experiments are reported. In the first, risk aversion is observed to increase with probabilities in the domain of gains</p>				
20. DISTRIBUTION/AVAILABILITY OF ABSTRACT <input type="checkbox"/> UNCLASSIFIED/UNLIMITED <input checked="" type="checkbox"/> SAME AS RPT <input type="checkbox"/> DTIC USERS			21. ABSTRACT SECURITY CLASSIFICATION Unclassified	
22a. NAME OF RESPONSIBLE INDIVIDUAL Robin M. Hogarth			22b. TELEPHONE (Include Area Code) 312-702-7271	22c. OFFICE SYMBOL

19. ABSTRACT

but to decrease for losses. There is also evidence of the predicted probability x payoff interactions for both losses and gains. The second experiment examines attitudes toward risk and ambiguity. For gains, risk and ambiguity aversion increase with both probabilities and payoffs. As predicted, there is a probability x payoff interaction on risk attitudes, but contrary to prediction, no interaction in respect of ambiguity. For losses, both risk and ambiguity aversion decrease with increases in probability as predicted, but the predicted effects for payoffs and probability x payoff interactions do not obtain. The theory and results are discussed in relation to other experimental evidence, alternative models of risky choice, and implications of venture theory for explaining other phenomena.

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Venture Theory: A Model of Decision Weights

Recent years have seen a surge of interest in models of risky decision making. (For overviews, see Schoemaker, 1982; Tversky & Kahneman, 1986; Fishburn, 1987; Machina, 1987; Weber & Camerer, 1987). Much of this research attempts to develop prescriptively appealing axioms for risky choice that can account for certain well-established paradoxes. In some cases, appeal is made to additional, psychological arguments such as notions of regret (see e.g., Bell, 1982; Loomes & Sugden, 1982). The present paper does not follow an axiomatic approach; nor is our intention prescriptive. Instead, we seek to develop a *descriptive* model that can account for choice behavior in a wide range of situations involving risk and uncertainty.

An important difference between the nature of the payoffs and probabilities that characterize most decisions is that whereas the former are typically *tangible* (e.g., money, goods, etc.), the latter can only be understood as *mental* constructs. One cannot touch, feel, or see a probability. In this paper we present a model of decision making called venture theory in which this distinction is explicitly recognized. We model the subjective evaluation of decision outcomes by psychophysical functions while the weights given to probabilities are conceptualized as the end result of mental processes that reflect both cognitive and motivational factors. Specifically, venture theory uses the value function proposed in Kahneman and Tversky's (1979) prospect theory and provides an account of how decision weights are influenced by variables that are both cognitive and motivational in origin. In common with many theories in which probabilities are "distorted" (see, e.g., Karmarkar, 1978; Quiggin, 1982), venture theory can be used to explain the well-known choice paradoxes such as those proposed by both Allais (1953) and Ellsberg (1961). However, such explanations are not the experimental focus of this paper. Instead we use venture theory to explore the nature of probability \times utility interactions.

The paper is organized as follows. We first discuss some of the issues underlying people's use of probabilistic information in risky decision making. This leads to the development of the

venture theory model of decision weights. By combining venture theory decision weights with the value function of prospect theory (Kahneman & Tversky, 1979), we make a series of predictions concerning attitudes toward risk and ambiguity as a function of different levels of probabilities and payoffs. These predictions are then tested in two experiments. Finally, we discuss venture theory in relation to (a) our own and other experimental findings, (b) alternative models of risky choice, and (c) implications for further work.

Probabilities \neq decision weights

To motivate our theory, consider first the distinction between the value assigned to receiving an outcome denoted x under conditions of both certainty and uncertainty. When certain of receiving the outcome, assume that the value assigned to it is $v(x)$ where $v(\cdot)$ represents a prospect theory value function (Kahneman & Tversky, 1979).¹ Assume further that under certainty of *not* receiving the outcome its value is 0. Thus, it is reasonable to conclude that the value of receiving the outcome under uncertainty lies somewhere between 0 and $v(x)$. This, in turn, implies that under uncertainty $v(x)$ has been discounted by some factor or "decision weight" that is bounded between 0 and 1. To those familiar with the axioms of decision theory, it seems natural to use probability as a decision weight. However, this hides important psychological concerns. These center on the meaning of probability, the effects of uncertainty or ambiguity about probability estimates, possible effects due to the sign and/or size of outcomes, and the distinction between certainty (i.e., probabilities of 1 or 0) and uncertainty (i.e., probabilities between 1 and 0).

The meaning of probability has long been controversial. Whereas subjectivists, following de Finetti (1937) and Savage (1954), are willing to equate probabilities with the general concept of "degrees of belief," we maintain that most people's intuitions about probabilities are more narrowly equated with the concept of long-run relative frequencies (cf. Lopes, 1981; Keren & Wagenaar, 1987). In teaching probabilistic concepts, for example, most introductory statistics texts use familiar gambling devices such as dice thereby implicitly, and often explicitly, motivating

the concept of probability as the limit of long-run relative frequency. In addition, when students first study expected utility theory (von Neumann & Morgenstern, 1947), many find the notion of applying the expected utility principle to one-shot as well as multiple plays of a gamble counterintuitive. In other words, whereas the use of probability as a decision weight is intuitively appealing when considering the value of multiple plays of a gamble, this notion does not have the same appeal for single-shot gambles. To illustrate, consider the difference in observable outcomes between playing, once and many times, a gamble characterized by a p -chance of winning $\$x$ and a $(1-p)$ chance of $\$0$. In the multiple-shot case, whereas many different outcomes are possible, it is highly probable that the *net* outcome will be close to the expected value, and more so the greater the number of plays. Thus, the use of probability as a decision weight in characterizing the net expected outcome does correspond to some physical reality. In contrast, a similar calculation in the single-shot case has little meaning in that the extreme values of $\$x$ and $\$0$ are the only two possible outcomes. From a *psychological* viewpoint, therefore, there is greater uncertainty concerning the *outcome of a single gamble* as opposed to the net outcome of multiple plays even when the probability determining outcomes is the same in both cases. In what follows, we refer to this additional source of uncertainty as *outcome uncertainty*.

In experimental work on risky decision making, probabilities are typically provided or assumed to be known with precision. However, this contrasts with experience in the real world which is more commonly characterized by vagueness or ambiguity concerning probabilities. Moreover, as originally demonstrated by Ellsberg (1961), people do not weight known and ambiguous probabilities equally in choice (see also Einhorn & Hogarth, 1985; 1986). Thus, any theory of decision weights must also account for the effects of *ambiguity* or vagueness about probabilities.

There is a common intuition that the nature of outcomes (i.e., sign and size of payoffs) can affect the weight given to probabilities in decision making. Indeed, from a prescriptive viewpoint an advantage of expected utility theory is that it exhorts people to assess probabilities and utilities

independently in order to avoid the traps of "wishful thinking" or "persecution mania."

Descriptively, the nature of probability \times utility interactions has been hard to specify from empirical studies. Some researchers (e.g., Edwards, 1962) have argued for the existence of effects due to sign of payoff but not size; however, since theories have not explicitly predicted when and where such interactions might occur, the evidence for or against interactions is hard to evaluate. We shall argue that payoffs do exert an influence on decision weights but that, in some circumstances, these effects are offset by other variables.

Finally, we believe that there are important psychological differences between situations involving uncertainty (i.e., probabilities between 0 and 1) and certainty (i.e., probabilities of 0 and 1). Specifically, we hypothesize that people's decision weights exhibit particular attraction toward certainty of gaining rewards and aversion to certainty of incurring losses (cf. Kahneman & Tversky, 1984).

The decision weight model

The process underlying venture theory is similar to the ambiguity model proposed by Einhorn and Hogarth (1985; 1986). See also Hogarth (1987). The key notion is that decision weights used to discount values of outcomes for uncertainty are the end result of a process that involves first anchoring on an estimate of probability and then adjusting this by imagining other possible values for the weights. In the typical experimental task, the anchor is the probability supplied by the experimenter; in more realistic situations, it could be a figure suggested by experience, an estimate provided by an expert or from statistical data, and so on. The adjustment is the net effect of a mental simulation process in which the decision maker "tries out" various weights suggested by different possible scenarios.²

To illustrate, imagine a person faced with a .5 chance of winning \$1,000 (and a .5 chance of \$0) in a simple one-shot gamble. First, note that this situation is characterized by outcome uncertainty in that although the probability of winning is .5, the outcome can only be either \$1,000

or \$0. Indeed, it is the presence of outcome uncertainty that encourages mental simulation of different possible decision weights. Second, when faced with a gamble of this type one would not necessarily expect that equal weight be accorded in imagination to values above and below .5. In fact, assuming caution in the face of risk, more weight would be given to possible values below rather than above .5. More generally, we shall assume that both the sign and size of the payoff affect the extent to which differential weight is given to values above and below the anchor. Finally, consider the situation where .5 is the best estimate of an ambiguous probability. Relative to cases involving known probabilities, ambiguity would increase uncertainty thereby inducing more simulation of alternative decision weights.

This process can be represented algebraically in the form

$$Z(p_A) = p_A + (k_g - k_s) \quad (1)$$

where p_A is the anchor, k_g represents the values and weight accorded in the mental simulation to values greater than the anchor, and k_s corresponds to the weighted values below the anchor.

To make the model operational, it is necessary to specify (1) how the anchor, p_A , is established, (2) what affects the *amount* of mental simulation (i.e., the ranges of alternative values considered), and (3) what determines the *sign* or direction of the adjustment process.

(1) As implied in the example given above, when the probability of obtaining an outcome is known, this forms the anchor. In ambiguous circumstances, the anchor is assumed to be some initial value of the probability that is typically available to the decision maker. This may be a figure based on historical data, provided by experts, or selected from memory.

(2) The amount of mental simulation is assumed to increase with both outcome uncertainty and ambiguity. Consider first the effect of outcome uncertainty when there is no ambiguity about probabilities. For a two-outcome gamble, there is no outcome uncertainty when the probability of obtaining one of the outcomes is known to be either 0 or 1. For a probability of .5, however,

outcome uncertainty is maximized. Thus both outcome uncertainty and mental simulation increase from 0 to a maximum as the probability increases from 0 to .5 and decreases from 1 to .5. Since ambiguity increases uncertainty about the probabilities, this, in turn, increases the amount of mental simulation over and above the non-ambiguous case. In short, it is assumed that the amount of simulation increases with the amount of perceived ambiguity. However, it is important to note that, unlike outcome uncertainty, anchors of 0 or 1 do not imply lack of mental simulation in the presence of ambiguity.

(3) The sign, or net effect of the adjustment process (i.e., $k_g - k_s$), reflects two factors. These are (a) the location of p_A , and (b) the relative weight given to imagined values above and below the anchor. The location of p_A affects the net effect of the adjustment process in that, if $p_A = 0$, the adjustment must be nonnegative, and nonpositive if $p_A = 1$. It also follows that for small values of p_A there is a greater range of values that can be imagined above the anchor than below it; for large values of p_A , it is the reverse.

Two kinds of variable can affect the weighting of values above and below the anchor. First, there are individual differences. When assessing the chances of obtaining a good outcome (e.g., a large sum of money), people may differ in the extent to which they imagine values above and below the anchor. Second, differential weight also reflects the context of the decision. In this paper, we assume that people are cautious rather than reckless when taking decisions under uncertainty (see, e.g., the literature on "defensive pessimism," Norem & Cantor, 1986a; 1986b). For decisions involving good or positive payoffs, therefore, values greater than the anchor are underweighted relative to those below. Conversely, bad or negative payoffs imply that greater weight is accorded to values above rather than below the anchor. We further assume that the absolute size of payoffs affects imagination. This means that, for positive payoffs, as the stakes increase more weight is given to possible values below the anchor; for negative payoffs, however, increasing stakes imply that more weight is given to values above the anchor.

The assumptions concerning the sign and size of the adjustment in Equation 1, i.e.,

$(k_g - k_s)$, can be summarized by writing

$$k_g = f(\sigma, \theta, p_A, \rho) \quad (2a)$$

and

$$k_s = g(\sigma, \theta, p_A, \lambda) \quad (2b)$$

where both k_g and k_s are increasing functions of both outcome uncertainty (σ) and perceived ambiguity (θ), k_g is a decreasing function of p_A but k_s is an increasing function of p_A , and ρ and λ are parameters representing the weight given in imagination to values above and below the anchor, respectively. (As also assumed above, ρ and λ are increasing functions of the absolute sizes of payoffs).

Further specifications. Since the above functions are loosely specified, we now consider restrictions that correspond with the underlying psychological intuitions.

First, examine a situation in which there is no ambiguity and values above and below the anchor are weighted equally in imagination. In the absence of ambiguity, recall that we have already specified $Z(p_A) = 0$ when $p_A = 0$, and $Z(p_A) = 1$ when $p_A = 1$. However, how do other values of p_A relate to $Z(p_A)$? When $p_A = .5$, $k_g = k_s$ since the ranges of possible values above and below the anchor are identical; this also implies that $Z(p_A) = .5$ even though outcome uncertainty is maximized. Now consider $Z(p_A)$ for values corresponding to p_A between 0 and .5 and note this is affected by two conflicting forces. First, as p_A increases, so does outcome uncertainty. This has the effect of increasing the difference between $Z(p_A)$ and p_A (i.e., $k_g - k_s$) which must be positive since there are more values above the anchor than below; second, as p_A increases, the range of values above the anchor decreases relative to those below thereby decreasing the difference between k_g and k_s . The net effect is that, for $0 < p_A < .5$, $Z(p_A)$ is a concave function of p_A . By an analogous argument it follows that, for $.5 < p_A < 1$, $Z(p_A)$ must be a convex function of p_A . Thus, in the absence of ambiguity, when equal weight is given to values

imagined above and below the anchor, the function relating $Z(p_A)$ to p_A is concave below .5 and convex above as illustrated in Figure 1a.

 Insert Figure 1 about here

Now consider the case where $p_A = .5$ and values below the anchor are weighted more heavily in imagination than those above. Here $Z(p_A) < p_A$ since although the ranges of possible values on both sides of the anchor are equal, those below are weighted more heavily. However, there will be a point between $p_A = 0$ and $p_A = .5$ where $Z(p_A) = p_A$. This point, labeled p_C (to denote "cross over") occurs when the additional weight given to values below the anchor (relative to those above) exactly compensates for the fact that the range of possible values below the anchor is smaller than that above such that $k_g = k_s$. Moreover, for $p_A < p_C$, $Z(p_A) > p_A$ since the greater range of possible values above p_A relative to those below "overcompensates" for the direction of differential weighting. It also follows that as greater weight is accorded to values below rather than above the anchor, the more the crossover point approaches 0. Figure 1b shows the extrapolation of this reasoning in graphical form. Following analogous arguments, Figure 1c shows that the crossover point, p_C , is greater than .5 if values above the anchor are weighted more heavily in imagination than those below.

To model the effects of ambiguity, recall that this increases the amount of mental simulation and thus the extent to which $Z(p_A)$ deviates from p_A . First, consider the $Z(p_A)$ values associated with anchors of 0 and 1. In the presence of ambiguity, these are adjusted, up for $p_A = 0$, and down for $p_A = 1$. Moreover, the amount of the adjustment reflects the degree of perceived ambiguity. (In thinking through this, ask yourself: Would you prefer having a "known zero" chance of winning a prize as opposed to an "ambiguous zero" chance?) In the interest of symmetry, assume that the amount by which $Z(p_A)$ overweights p_A when $p_A = 0$ is the same as the amount of underweighting when $p_A = 1$. Second, note that for values of p_A below p_C , the

function incorporating effects of ambiguity will lie above one that does not; for values above p_c , it is the reverse. These effects are illustrated in the five panels of Figure 2 which show the effects of ambiguity for different values of p_c .

 Insert Figure 2 about here

Whereas "venture functions" may take several forms, it is reasonable to restrict them in two ways. First, there is a unique crossover point; second, for $0 < p_c < .5$ and $.5 < p_c < 1$ the $Z(p_A)$ values of complementary anchors, i.e., p_A and $(1-p_A)$, do not sum to 1. For the former, $Z(p_A) + Z(1-p_A) < 1$; for the latter, $Z(p_A) + Z(1-p_A) > 1$. Although not severe, these restrictions are important in that nonadditive decision weights can be used to "explain" many anomalies of standard choice theory.

Implications. There are several implications of the model. First, note that the venture function is regressive with respect to p_A . In general, for $0 < p_A < 1$, the function starts by "overweighting," has a crossover point (p_c), and then "underweights" the anchor. The location of the cross over depends on the relative weight given in imagination to values of possible decision weights above and below the anchor. This, in turn, is assumed to depend on both the sign and size of payoffs such that, for positive payoffs, $p_c < .5$ and is smaller the larger the stakes; for negative payoffs, $p_c > .5$ and is larger the greater the absolute size of the payoff. Incidentally, it should be noted that the venture function illustrated in Figure 1a is similar to the models proposed by both Karmarkar (1978) and Quiggin (1982). In addition, by fitting responses to a series of questions given in the 1950's to several illustrious subjects (including de Finetti and Malinvaud), Allais (1986) has developed a three-parameter model that yields curves similar to those of venture theory. In fact, his empirical results for positive payoffs indicate curves similar to that illustrated in Figure 1b.

Second, in the absence of ambiguity, the venture function, unlike the π -function of prospect

theory, is continuous between 0 and 1. Note, however, that the function is particularly steep as it approaches both 0 and 1 thereby capturing the notions of attraction toward certainty of gaining rewards and aversion to certainty of incurring losses.

Third, the extent to which $Z(p_A)$ deviates from p_A over the range of the latter depends on both outcome uncertainty and the amount of perceived ambiguity, i.e., the greater the mental simulation induced by these factors, the greater the deviation.³

Fourth, except for cases where $p_A = 0$ or .5 or 1, decision weights associated with complementary probabilities do not sum to 1. $Z(p_A)$ values are typically subadditive when decision makers are confronted with gains (i.e., for $0 < p_c < .5$), but superadditive in the face of losses (i.e., for $.5 < p_c < 1$).

Fifth, the model can be used to predict how attitudes toward risk and ambiguity vary as a function of sign and size of payoffs as well as levels of probability. We now turn to these predictions.

Attitudes toward risk and ambiguity

The predictions made below correspond to expectations concerning the modal behavior of subjects since it is assumed that all subjects have the same attitude of caution ("defensive pessimism") in the face of risk and ambiguity. Attitudes toward risk and ambiguity are defined with respect to specific choices. Thus, a choice is said to be risk averse if a person prefers a sure amount equal to the expected value of a gamble to the gamble itself, and ambiguity averse if a gamble with a known probability is preferred to one involving an uncertain probability that has been equated in other respects with the known probability. By extension, the terms risk- and ambiguity seeking are the contrary of risk- and ambiguity averse. The statement that, for example, risk aversion increases as a function of a given variable, is taken to mean that, in a sample of individuals, the observed proportion of risk averse choices increases with that variable.

It is instructive to consider predicted attitudes toward risk and ambiguity separately for gains

and losses. For gains, there are two forces that induce tendencies toward risk aversion. These are the concavity of the prospect theory value function, and the general underweighting of probabilities implied by the venture function. Thus, risk aversion is predicted to increase as both levels of probabilities and payoffs increase. That is, for $0 < p_c < .5$, whereas small probabilities can be overweighted (thereby implying a force toward risk seeking), underweighting predominates as probabilities increase -- see Figure 1b. In addition, the effect of increasing payoffs is to lower p_c such that the range of probabilities over which underweighting occurs is greater for large as opposed to small payoffs. These predictions in respect of probabilities and payoffs are identified as Predictions 1 and 2, respectively, and are summarized in Table 1 along with other predictions detailed below.

Insert Table 1 and Figure 3 about here

The effects of payoff size on risk attitudes can be further illuminated by considering Figure 3a which shows three venture functions that differ only in their p_c values. These functions are drawn to approximate venture functions applicable to small ($p_c \equiv .5$), intermediate ($0 < p_c < .5$), and large ($p_c \equiv 0$) positive payoffs. As discussed above, the functions show that differences in risk attitudes could exist between small and large payoffs. However, they also imply that differences in risk attitudes due to size of payoff vary with probability level in that, excluding extremely small and large probabilities, differences between the functions are greater for small as opposed to large probabilities. In other words, venture theory predicts that differences in risk attitudes between small and large payoffs are expected to decrease as probabilities increase (excluding, of course, very large or small probabilities) -- Prediction 3.

Predictions concerning the effects of payoffs and probabilities on attitudes toward ambiguity can be inferred by consulting Figure 2. Ambiguity aversion in the domain of gains is expected to:

- (i) increase with probability level -- Prediction 4. Note that Figures 2b and 2c exhibit ambiguity

seeking for low but not large probabilities; (ii) increase with payoff size -- Prediction 5. Observe that ambiguity seeking decreases as p_c becomes smaller; and (iii) be more sensitive to payoff size at low as opposed to high levels of probability -- Prediction 6. For $p_c > .5$, there are few differences between Figures 2a, 2b, and 2c.

For losses, there are two forces that conflict in their impact on risk attitudes. On the one hand, the convex nature of the prospect theory value function over losses implies risk seeking. On the other, since $p_c > .5$ for losses, probabilities are generally overweighted thereby implying a force toward risk aversion.

Effects of probabilities and payoffs on risk attitudes can be predicted by considering Figure 3b which shows three venture functions applicable to small ($p_c \equiv .5$), intermediate ($.5 < p_c < 1$), and large ($p_c \equiv 1$) negative payoffs. Examination of Figure 3b leads to the following predictions: (i) decreasing risk aversion as probabilities increase -- Prediction 7; (ii) increases in risk aversion as payoffs increase -- Prediction 8; and, since Figure 3b is a mirror image of Figure 3a, (iii) greater effects of payoffs on risk attitudes at large as opposed to small probability levels -- Prediction 9.

By consulting Figures 2c, 2d, and 2e, the effects of payoffs and probabilities on attitudes toward ambiguity in the domain of losses can be inferred. These are that ambiguity aversion is expected to: (i) decrease as probabilities increase -- Prediction 10; (ii) increase as absolute size of payoffs increases -- Prediction 11; and (iii) be more sensitive to payoff size at high as opposed to low levels of probability -- Prediction 12.

Finally, it is important to note that predictions concerning losses have been made in "mirror image" fashion to those concerning gains. However, recall that contrary to attitudes toward risk and ambiguity on the gain side, attitudes in respect of losses are postulated to result from conflicting forces (i.e., the convex shape of the value function and general overweighting of probabilities). As a consequence, one would expect the predicted modal patterns of choice to be less evident for losses as opposed to gains.

To test predictions concerning the effects of payoffs and probabilities on risk attitudes, it is

important to vary independently both payoffs and probabilities. To achieve this, two experiments were performed. In the first, payoffs were varied at different probability levels; in the second, probabilities were varied across two different payoff levels (small and large). Ambiguity was also manipulated in the second experiment.

Experiment 1

Task. The experimental stimuli were hypothetical gambles involving choices between, on the one hand, a p chance at winning (losing) $\$x$ and a $(1-p)$ chance of $\$0$, and, on the other hand, a riskless amount equal to the expected value of the gamble, i.e. $p.\$x$. Three probability levels were investigated, .10, .50, and .80 with three payoff levels corresponding to expected values of $\$2$, $\$200$, and $\$20,000$ (i.e., low, medium, and high payoffs). There were thus 9 choices to be made in respect of gains (3 probability levels \times 3 payoff levels) and 9 choices in respect of losses.

Subjects and Method. Subjects were 96 graduate and undergraduate students recruited through advertisements on the university campus. They were paid at the rate of $\$5$ per hour to participate in this and other experiments on decision making in a laboratory setting. Each subject responded to all 18 choices which were presented in random order in an experimental booklet. There were 3 possible responses for each choice: prefer the gamble (risky choice); prefer the riskless amount (i.e., sure thing); or indifference.

Results. Results are presented in Table 1. It is important to realize that probabilities and payoffs were *not* varied factorially in this experiment and that the design implies a negative correlation between payoff size and probability. For example, for the $\$20,000$ sure win subjects were faced with a .10 chance of winning $\$200,000$, a .50 chance of winning $\$40,000$, and a .80 chance of winning $\$25,000$. Thus, since probabilities have been held constant and outcomes varied, the relevant comparisons are *down the columns* within each probability level. This means that the data can only be used to make formal tests of Predictions 2 and 8 (see Table 1) concerning the effects of payoffs on attitudes toward risk. However, the results can also suggest whether the

predicted probability x payoff interactions occur (Predictions 3 and 9).

 Insert Table 2 and Figure 4 about here

The results for gains demonstrate the predicted effect of size of outcomes on attitudes toward risk (Prediction 2) and are illustrated in Figure 4a which shows, for each of the three probability levels, the numbers of subjects choosing the sure thing at each level of the latter. Note that at each of the 3 probability levels, risk averse behavior (i.e., proportion of subjects choosing the sure thing) increases as payoffs increase ($p < .0001$ by Cochran's test at all 3 probability levels).⁴ For example, from the greater detail provided in Table 2, note that at the .10 probability level, 25 subjects prefer the sure thing at \$2 and this number increases to 88 for \$20,000. The same pattern occurs at the .50 probability level (24 to 77), and again at .80 (34 to 66). However, at the .80 probability level there is little difference in risk attitudes between the sure things involving \$200 and \$20,000. Note too, that although probabilities and payoffs were not varied factorially, the results do suggest the presence of the predicted probability x payoff level interaction on risk attitudes, i.e., Prediction 3. Specifically, the differences between the numbers of subjects who are risk-averse at the three payoff levels decrease as probabilities increase (see Table 2). For example, between the \$2 and \$200 sure thing conditions, there are an additional 50 subjects (i.e., 75-25) who become risk-averse; however, the increases at the .50 and .80 levels involve 35 (i.e., 59-24) and 26 (i.e., 60-34) persons, respectively.

For losses, the pattern of results is less apparent than for gains and is illustrated in Figure 4b. However, risk averse behavior is observed to increase as payoffs increase (Prediction 8) and there is suggestive evidence of the predicted interaction between payoff levels and probability (Prediction 9). These effects are demonstrated by the lack of an effect of payoff size on risk attitudes at the .10 probability level (Cochran's test, $df=2$, $Q=2.48$, $p=.289$), but increasing risk-averse behavior (i.e., proportion of subjects choosing the sure thing) at .50 and .80 ($p < .0005$ by Cochran's test at both

levels) -- see Table 2 and Figure 4b. Consider, for instance, the differences between the numbers of subjects choosing the sure thing for the low and medium losses (21 vs. 40, and 10 vs. 31, respectively). There is, however, no difference between the medium and high payoffs.

Experiment 2

Task. Subjects were required to rank 3 possible options. These were: (1) choosing a certain sum (i.e. sure thing); (2) selecting a ball at random from an urn (designated #1) where the prize was contingent on drawing a ball of a specified color (with zero otherwise) and where the composition of the urn (numbers of balls and their colors) was known, i.e., choice with known probability; and (3) selecting a ball at random from an urn (designated #2) where the prize was contingent on drawing a ball of a specified color (with zero otherwise) but where the composition of the urn was not specified, i.e., choice with ambiguous probability. To operationalize ambiguity in the third option, subjects were told "Imagine that you have been allowed to view the contents of Urn #2 for a few seconds. You estimate that it contains balls but are not too sure of your estimate." The task was constructed so that, for each choice, the sure thing was equal to the expected value of drawing a ball at random from the urn with known composition. Moreover, the estimate of the number of winning balls in the ambiguous urn was equal to the number of winning balls in the urn of known composition.⁵

The design of the study involved a factorial arrangement of three within-subject variables; size of payoffs, probabilities, and sign of payoffs. There were 2 levels of payoff, small (\$1) and large (\$10,000); 3 probability levels, .10, .50, and .90; and versions involving both gains and losses. Each subject therefore faced 12 choice situations (i.e., $2 \times 3 \times 2$). The design of this experiment therefore permits testing Predictions 1 through 12.

Subjects and Method. There were 146 subjects from the same population as Experiment 1, recruited and remunerated in similar manner. Subjects responded to the stimuli presented on the screen of a microcomputer. However, these were not all presented in sequence; instead, blocks of

stimuli were interspersed between other decision-making tasks. For 82 of the subjects, the stimuli were presented in the same random order; the remaining 64 subjects saw the stimuli in individually randomized orders. Since this difference in method made no difference to results, it is ignored in the subsequent analysis.

Results. Figures 5a and 5b summarize the results of the experiment by plotting the percentage of subjects whose choices were risk- and ambiguity averse, respectively, as a function of probability levels, sign of payoff (gain or loss), and size of payoff (large or small).

 Insert Figures 5a and 5b about here

Consider the results in respect of risk attitudes toward gains. As shown in Figure 5a, these conform with venture theory in that risk-averse behavior increases with both probabilities (Prediction 1) and payoffs (Prediction 2), and differences in risk attitudes between the two payoff conditions are greater at the low as opposed to the high probability levels (Prediction 3). For example, with small payoffs (\$1) 20% of subjects exhibit risk-averse behavior at the .10 probability level and this rises to 53% at the .90 level. However, the corresponding figures are 80% and 84% for large gains (\$10,000). (Cochran's test shows significant effects across probability levels for small gains, $Q=40.29$, $df=2$, $p < .0001$, but not large gains, $Q=0.73$, $df=2$, $p = .694$).⁶

Across probability levels, increases in ambiguity-averse behavior are also observed -- see Figure 5b ($p < .0001$ by Cochran's test for both large and small gains). There are also small but statistically significant effects due to payoff size (Cochran's test of differences between payoff sizes at the .10, .50, and .90 probability levels gave values, $df=1$, of $Q=3.46$, $p=.063$; $Q=6.82$, $p=.009$; and $Q=3.52$, $p=.061$, respectively). However, there is no interaction between payoff size and probabilities. Thus, whereas the data support Predictions 4 and 5, Prediction 6 is not validated.

For losses, the data summarized in Figures 5a and 5b show both decreasing risk and

ambiguity aversion as probabilities increase ($p < .001$ by Cochran's test for both large and small losses), but no effects for differences in payoff size, and no probability \times payoff interactions.⁷ Thus, whereas Predictions 7 and 10 were validated, Predictions 8, 9, 11, and 12 were not.

Since, in this experiment, attitudes toward risk and ambiguity were simultaneously measured within subjects, it is of interest to ask whether these attitudes were correlated. In general, the data revealed no consistent pattern in that, on average, across all 12 conditions of the experiment, subjects' attitudes toward risk and ambiguity only coincide (i.e., are both risk- and ambiguity averse or risk- and ambiguity seeking) 55% of times. However, there are exceptions that fit the modal pattern suggested by venture theory. For example, for large positive payoffs, 73% of subjects were both risk- and ambiguity-averse at the high probability level (.90); conversely, for low negative payoffs, 47% of subjects were both risk- and ambiguity seeking at the high probability level.

Discussion of Experiments 1 and 2

In Experiment 1, risk attitudes were investigated for different payoffs holding probabilities constant. In Experiment 2, attitudes toward both risk and ambiguity were investigated, and the design permitted investigation of effects due to both probabilities and payoffs.

To summarize the results, the outcomes of Experiment 1 were consistent with venture theory's predictions. Main effects of payoffs on risk attitudes were observed for both gains and losses, and there was support for the predicted interaction between probabilities and payoffs, also for both gains and losses. As also predicted, the modal pattern of results was more marked for gains than for losses.

Results of Experiment 2 were more equivocal vis-à-vis the theory. Whereas the predicted main effects of probabilities on attitudes toward both risk and ambiguity were observed for gains and losses, this was not the case for payoffs. On the gain side, payoffs were seen to have significant main effects on both attitudes toward risk and ambiguity; however, although attitudes

toward risk exhibited the predicted payoff \times probability interaction, this did not occur for ambiguity. For losses, there were no main effects of payoff on attitudes toward either risk or ambiguity nor any payoff \times probability interactions.

What is(are) the source(s) of the partial inconsistency in results between the two experiments? Candidates for investigation include differences in the tasks, the fact that simple choices do not always provide sensitive measures of attitudes toward risk and ambiguity, the possibility that both tasks involved hypothetical gambles, and the role of individual differences. It is well known that risk attitudes exhibit considerable variability across different tasks (Fischhoff, Slovic & Lichtenstein, 1980) and this is probably also true of attitudes toward ambiguity.

It is important to emphasize that the venture theory predictions were made using only broad, directional assumptions concerning the functional dependence of p_c on payoffs. However, attitudes toward risk and ambiguity are quite sensitive to the location of p_c . To appreciate this, reconsider Figure 3 which illustrates venture functions for extreme and intermediate payoffs. Note from Figure 3 that, whereas the general nature of our predictions holds for differences in the p_c 's associated with payoffs, the effect of such differences in observable choice data is quite sensitive to the actual magnitude of the differences between p_c 's. In particular, small differences in p_c associated with different levels of payoffs might not yield significant differences in attitudes toward risk and ambiguity. An important issue for further work, therefore, is to determine the nature of the relation between p_c and the different levels of positive and negative payoffs. For example, a possible interpretation of Experiment 2 is that p_c is much more sensitive to differences in payoff levels for gains as opposed to losses.

Some results obtained here are consistent with others reported in the literature. Several investigators, for example, have noted increasing risk aversion on the gain side associated with increases in probability levels (see, e.g., McCord & de Neufville, 1984); others have found that attitudes toward risk on the loss side are less sensitive to differences in probability levels than occurs for gains (Cohen, Jaffray, & Said, 1985); and differences in risk attitudes due to the sign of

payoffs have been noted in many studies. There is also other evidence that probability weighting functions differ in respect of losses and gains (see e.g., Marks, 1951; Irwin, 1953; Nygren & Isen, 1985). However, in an attempt to calibrate prospect theory π -functions, Currim and Sarin (1987) report data contrary to venture theory in that π -functions for losses gave smaller $\pi(p)$ values at the same levels of p as π -functions for gains. In calibrating these π -functions, it is noteworthy that Currim and Sarin (1987) used questions involving consumer choices rather than laboratory-style gambles. This therefore raises the important issue of how contextual variables might affect venture functions.

General discussion

The experimental evidence supports a model that combines the value function of prospect theory with venture theory decision weights. Our discussion is organized around three topics: (a) further comments on our experimental evidence; (b) the relation of venture theory to other models of risky choice; and (c) implications of venture theory for explaining other phenomena.

Experimental evidence. There were two areas in which the venture theory predictions were not strongly supported by the data in this paper. First, although Experiment 1 showed the predicted effects of payoff size on attitudes toward risk for losses, there was no effect in Experiment 2. Other investigators have also reported conflicting evidence concerning the impact of payoffs on decision weights (see, e.g., Goldstein, Levi, & Coombs, 1987). However, contrary to previous experimental work aimed at detecting utility \times probability interactions, the research strategy adopted here was to use a theoretical model that explicitly suggested where such effects would be most likely to occur. Moreover, this model suggested that, in terms of attitudes toward risk and ambiguity, the net effect of different payoff levels on decision weights implies a highly interactive pattern of outcomes. Recall too, that according to venture theory, there is a key difference between risk attitudes toward gains and losses. For gains, two complementary forces shape risk attitudes (i.e., concavity of the value function and the effects of caution on decision

weights); however, for losses the forces implied by the value function and decision weights conflict. Thus, by their very nature, attitudes toward risk on the loss side may be inherently inconsistent. At the very least, our analysis of the effects of payoffs on decision weights illuminates the complexity of this phenomenon.

In this paper, the venture theory predictions assumed that all subjects had the same personal disposition or attitude of caution in the face of risk. In other words, we were predicting modal behavior under the assumption that most people approach risky situations from the viewpoint of "defensive pessimism." However, it is more realistic to assume that people vary on a pessimism-optimism continuum (Norem & Cantor, 1986a; 1986b). Indeed, as demonstrated by Schneider and Lopes (1986) (see also Lopes, 1987), when subjects are selected on the basis of previously determined risk attitudes, the choices of "risk-averse" and "risk-seeking" subjects differ systematically when faced with a new series of risky problems. Specifically, these investigators' data are consistent with Lopes' (1987) two-factor theory whereby, for risk-averse subjects, risk aversion in the domain of gains results from positive correlation between the two forces of "security-potential" and "aspiration level;" however, these same two forces conflict in determining attitudes toward losses. For risk-seeking subjects, on the other hand, it is the reverse: conflict on the gain side, but no conflict concerning losses. Thus, unless one has prior knowledge concerning the risk tendencies of subjects, analysis that assumes a modal attitude toward risk must be incomplete.

It is straightforward within venture theory to model optimism (as opposed to caution) such that the conflict between forces that produce risk attitudes reflect in the same way as in Lopes' (1987) model. Within venture theory, one simply reverses the assumptions that determine the location of p_c such that, for example, Figure 1c would depict an optimist's function for gains and Figure 1b that for losses. This means that when these functions are combined with the prospect theory value function, the shapes of the venture and value functions would both favor risk seeking over losses but conflict with respect to risk attitudes toward gains. In a given population,

however, we note that it would be problematic to know the proportions of people who were primarily optimistic, pessimistic or unstable in this respect. The risk-averse and risk-seeking subjects examined by Schneider and Lopes (1986), it should be noted, were preselected from the extremes of a large subject pool (greater than 1,000).

In Experiment 2, the second inconsistency with venture theory predictions was that ambiguity was not seen to vary with payoff size for losses and to show only moderate effects for gains. At first sight, this might imply that attitudes toward ambiguity are not sensitive to size of payoff. However, in a recent study of professional actuaries, Hogarth and Kunreuther (1988) varied probability levels, payoff size, ambiguity, and type of risk (independent versus correlated) in a factorial design concerning the pricing of a warranty. In addition to significant main effects for probability level and ambiguity, their data revealed a significant main effect for independent versus correlated risks (which proxies for payoff size by varying the potential loss at stake) and an interaction between payoff size and ambiguity. Thus, although similar effects were not found in Experiment 2, it cannot be said that they do not exist. Moreover, in other studies of insurance decision making, Hogarth and Kunreuther (in press) have found that attitudes toward ambiguity are sensitive to the role a person takes in the situation, i.e., as the buyer or seller of insurance. It is possible that attitudes toward ambiguity are more sensitive to contextual variables than differences in payoff per se. Determining the relative impact of these variables is an important issue for future work.

Relations to other models of risky choice. The idea that "distortions of probability" can be exploited to explain deviations from expected utility theory is not new (see, e.g., Bernard, 1974). However, little attention has been paid to date as to *why* decision weights differ from probabilities.⁸ Although Kahneman and Tversky (1979; 1984) have provided some psychophysical arguments (see also Grossberg and Gutowski, 1987), Lopes (1987) points out these arguments reduce decisions concerning risk to a series of psychophysical reactions and leave no room for explanations of risky behavior that incorporate either emotive aspects such as fear or

cognitive processes involving, say, imagination. In other words, models based entirely on psychophysical notions would seem to eliminate a priori much that underlies the *psychology* of risk.

In constructing venture theory, we have assumed it is useful to model the evaluation of payoffs by a psychophysical function but have specifically conceptualized the determination of decision weights as the outcome of a mental process that is affected by both cognitive and motivational influences, i.e., imagination and payoffs. We believe that the roles of cognition and motivation become particularly important as one moves from studying gambles in stylized laboratory settings to decisions taken in more realistic settings where, although people may have knowledge about payoffs, information about uncertainties or probabilities is typically incomplete (March & Shapira, 1987).

Several other models involving decision weighting functions have attracted attention in the literature. These include the work of Karmarkar (1978), Quiggin (1982), and Yaari (1987) (for an overview, see Fishburn, 1986; 1987). Moreover, most of these models explain the "standard" paradoxes such as that of Allais (1953) (as can models using standard probabilities such as those of Chew & MacCrimmon, 1979, and Machina, 1982). However, the decision weight functions adopted by these researchers are restricted in ways that would not predict all the findings described in this paper. In the models of both Karmarkar (1978) and Quiggin (1982), for instance, the decision weight at $p = .5$ is constrained to equal $.5$. Like Tversky and Kahneman (1986), we also doubt whether one can capture most of the richness of choice behavior by way of axiomatically consistent theories of choice.⁹

As a guide to prescriptive decision making, the venture theory model has several unattractive features. Recall, however, that our intent is not to prescribe, but to describe and understand. A possibly disturbing feature of the model is that the venture function, $Z(p_A)$, is not necessarily a monotonic function of p_A such that it could on occasion predict violations of dominance in choice. In fact, in choice problems where dominance relations are transparent, we do not believe that

people will violate this normative principle (cf. Kahneman & Tversky, 1979). However, when the relation is not transparent or people make independent judgments of the value of uncertain outcomes, violations of dominance could still be expected to occur (for relevant experimental evidence, see Goldstein & Einhorn, 1987).

Further implications. Whereas both attitudes toward risk and ambiguity and the nature of probability \times utility interactions were the experimental focus of this paper, it is important to emphasize that venture theory can also "explain" the well-known choice paradoxes of Allais (1953) and Ellsberg (1961). However, since these paradoxes can also be accounted for by many other models, this no longer ranks as an important achievement (Hogarth, 1987). Of note, however, is that since venture theory explicitly allows for the effects of size of payoff, it can also be used to explain the fact that the rate of violation of the substitution axiom in the Allais paradox is greatly reduced for small as opposed to large payoffs (see, e.g., Wothke, 1985).

The structure of venture theory also allows explanations of contextual effects on decision making. To do this, however, it is first necessary to specify assumptions as to how, in specific circumstances, context affects the location of p_c by inducing differential weighting in imagination of possible values of decision weights above and below the anchor. In addition to the experimental results reported in this paper, the assumptions concerning modal behavior that we adopted can also be used to explain several puzzling results reported in the literature.

The simultaneous existence of gambling and the purchase of insurance has challenged many theorists working within the expected utility framework. This phenomenon can be explained within both venture theory and prospect theory by noting that small probabilities tend to be overweighted. However, prospect theory can not easily account for the findings of Hershey and Schoemaker (1980) who have shown systematic differences when the same economic choices are presented as gambles, on the one hand, or insurance contracts, on the other. Specifically, the gambling context induces less risk-averse behavior than insurance. Within venture theory, however, these findings are easily accommodated by noting that people are liable to have different attitudes toward

uncertainty when gambling as opposed to buying insurance even when economic incentives are equated. Thus, since the social context of insurance suggests caution (cf. Hershey & Schoemaker, 1980), it is reasonable to assume that more weight is given in imagination to values of possible decision weights above the anchor in the insurance as opposed to gambling scenarios such that $P_c(\text{insurance}) > P_c(\text{gambling})$ (recall one is dealing with probabilities of losses).

Venture theory also promises to provide an attractive means of exploring other phenomena. For example, when playing sequences of gambles people have been observed to change risk attitudes as a function of experiencing wins or losses (Thaler & Johnson, 1986; McGlothlin, 1956). Given the relatively small amounts of money involved in such gambles, it seems implausible to believe that this behavior can be explained by shifts in utility or value functions. In addition, explanations that posit changing reference points become somewhat involved. Instead, it seems more likely that past successes or failures lead to shifts in optimism or caution that affect the differential accessibility of scenarios people can imagine resulting from future gambles. In venture theory, differential weighting of such imaginary scenarios imply values of p_c that can change from trial to trial. Similarly, the puzzling effects of the manipulation of affect on risk attitudes might also be amenable to analysis by considering the likely impact of affect on p_c (see, e.g., Isen & Geva, 1987, and references). We stress, however, that in suggesting the analysis of these topics by means of venture theory, it is important to specify assumptions about differential weighting in imagination and its impact of p_c that can lead to experimental predictions. Given the flexibility inherent in the specification of venture theory, "explanations" of existing phenomena are relatively easy to construct.

One intriguing avenue of research is the role of individual differences in attitudes toward risk and ambiguity. As noted above, the presence of individual differences was marked in the studies reported here by considerable variation around the modal class of behavior predicted by venture theory. Indeed, this is not unusual in models of risky decision making and several researchers go so far as to report separate analysis for subjects who are predominantly risk-averse or risk-seeking

(e.g., Hershey & Schoemaker, 1985; Schneider & Lopes, 1986). To the extent that revealed p_c values capture systematic individual tendencies, venture theory is capable of accounting for individual differences. However, the problem, as in much research on this topic, is to find variables that can be reliably related to individual differences as opposed to classifying subjects on the basis of the very behavior being studied.

Finally, we note that the extensive literature on risky decision making relies heavily on stylized experimental gambles and, in particular, the explanation of a limited number of "paradoxical" findings. Indeed, an important cost of proposing a model of risky decision making is that one must, at least, be able to explain this literature. However, there is now growing awareness that the gambling metaphor of risky choice is limited in its application to many real world situations (cf. Lopes, 1983; March & Shapira, 1987). Since venture theory models how decision weights are affected by psychological constructs of emotion (e.g., caution) and cognition (e.g., imagination), we believe it provides a useful structure for studying the impact of uncertainty in a wide range of tasks both in and outside the psychological laboratory.

Footnotes

- * This work was supported by a contract from the Office of Naval Research and a grant from the Sloan Foundation. The authors are much indebted for comments on earlier versions of the paper to William Goldstein, Stephen Hoch, Joshua Klayman, George Loewenstein, and Paul Schoemaker. The comments and research assistance of both Brian Gibbs and Jay Koehler are also much appreciated.
- ¹ The characteristics of the prospect theory value function are: (i) outcomes are evaluated as gains or losses relative to a reference point; (ii) the function is concave over gains but convex over losses; and (iii) the function is steeper for losses than for gains. See Kahneman and Tversky (1979).
- ² The presentation and underlying rationale of the model are closely related to the development of the ambiguity model presented in Hogarth (1987).
- ³ Note that in the case of multiple plays of a gamble, outcome uncertainty is reduced. Thus, in the absence of ambiguity, $Z(p_A) \rightarrow p_A$ as the number of plays of the gamble increases. The limit of p_A would not, however, be reached in the case of ambiguity.
- ⁴ It is unclear how one should perform an analysis of variance with repeated measures on a 0-1 dependent variable. Thus, although we have performed several such analyses, we have adopted the conservative strategy of testing our hypotheses by reporting the results of specific contrasts based on Cochran's test. Substantive conclusions have not proved sensitive to the statistical procedures adopted.
- ⁵ Note that to equate the same beliefs about probability levels in the corresponding ambiguous and non-ambiguous conditions, we specifically endowed subjects in the ambiguous conditions with specific probabilistic beliefs. e.g., "you estimate that it contains....." (emphasis added here).
- ⁶ Once again, we describe the statistical tests of our hypotheses using Cochran's test. We also analyzed these data using methods analogous to analysis of variance for categorical variables. Whereas some doubts exist concerning the appropriateness of these types of analysis for our

data, substantive conclusions were not affected.

- 7 Due to a programming error, responses concerning losses provided by 17 subjects were lost. Data for losses therefore involve 129 as opposed to 146 subjects.
- 8 Note, however, that Rachlin et al. (1986) have analyzed prospect theory from a behaviorist viewpoint and shown a correspondence between prospect theory's decision weight function and behaviorist concepts.
- 9 See also comments by Tversky and Kahneman (1986, p. S259) concerning the "regret" models of Bell (1982) and Loomes and Sugden (1982).

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Table 1

Summary of venture theory predictions concerning attitudes toward risk and ambiguity

Gains

Attitudes toward risk.

1. Main effect for probability: The proportion of risk averse choices is predicted to increase as probabilities increase.
2. Main effect for payoffs: The proportion of risk averse choices is predicted to increase as payoffs increase.
3. Probability x payoff interaction: Differences in risk attitudes between small and large payoffs are expected to decrease as probabilities increase.

Attitudes toward ambiguity.

4. Main effect for probability: The proportion of ambiguity averse choices is predicted to increase as probabilities increase.
5. Main effect for payoffs: The proportion of ambiguity averse choices is predicted to increase as payoffs increase.
6. Probability x payoff interaction: Effects of payoff size on attitudes toward ambiguity are predicted to be pronounced for small as opposed to large probabilities.

Losses

Attitudes toward risk.

7. Main effect for probability: The proportion of risk averse choices is predicted to decrease as probabilities increase.
8. Main effect for payoffs: The proportion of risk averse choices is predicted to increase as the absolute size of payoffs increases.
9. Probability x payoff interaction: Differences in risk attitudes between small and large payoffs are expected to increase as probabilities increase.

Attitudes toward ambiguity.

10. Main effect for probability: The proportion of ambiguity averse choices is predicted to decrease as probabilities increase.
11. Main effect for payoffs: The proportion of ambiguity averse choices is predicted to increase as the absolute size of payoffs increases.
12. Probability x payoff interaction: Effects of payoff size on attitudes toward ambiguity are predicted to be pronounced for large as opposed to small probabilities.

Note: Since, contrary to attitudes in the domain of gains, revealed attitudes in the domain of losses are postulated to result from conflicting sources, more confidence is accorded to observing the predictions for gains as opposed to losses.

Table 2

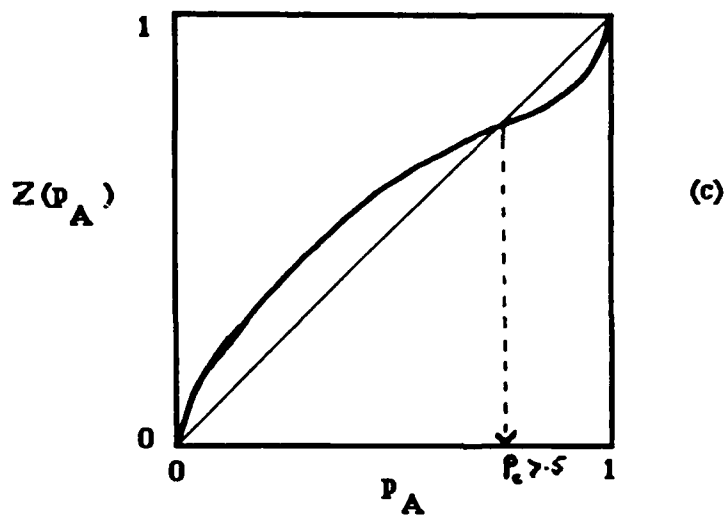
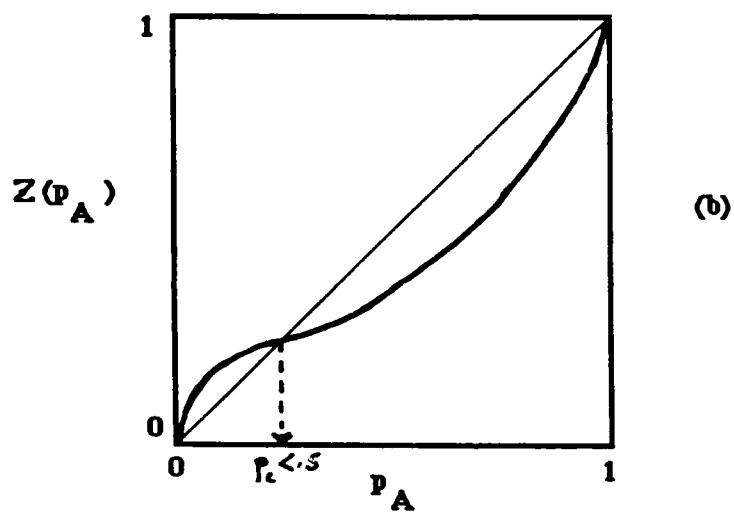
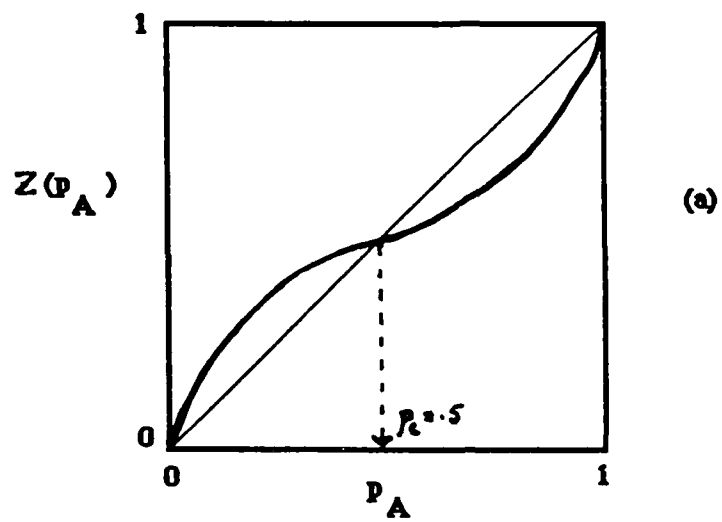
Experiment 1: Choices made by subjects in all conditions

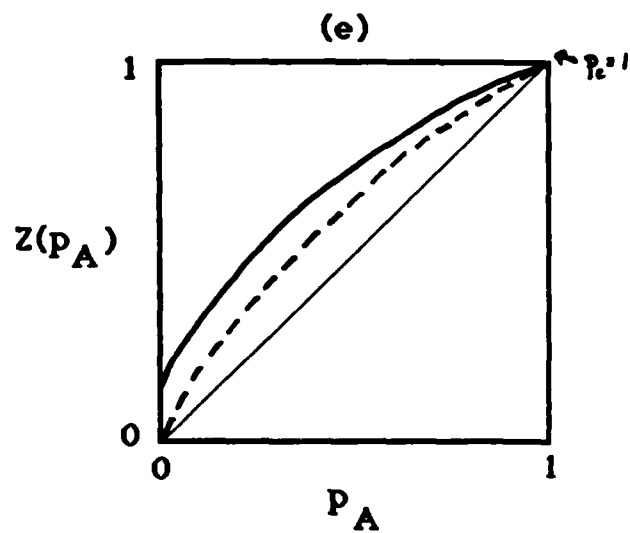
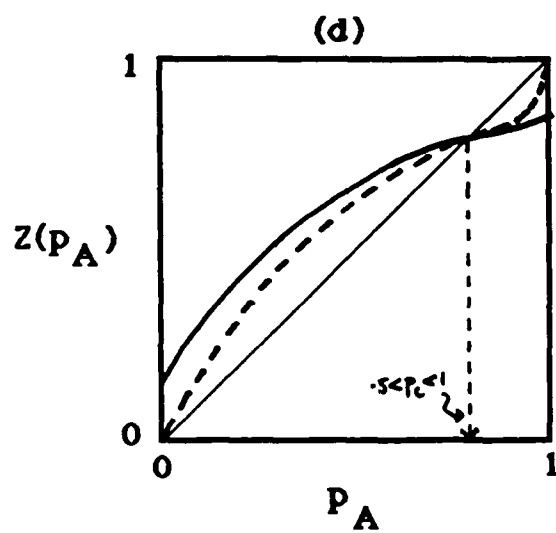
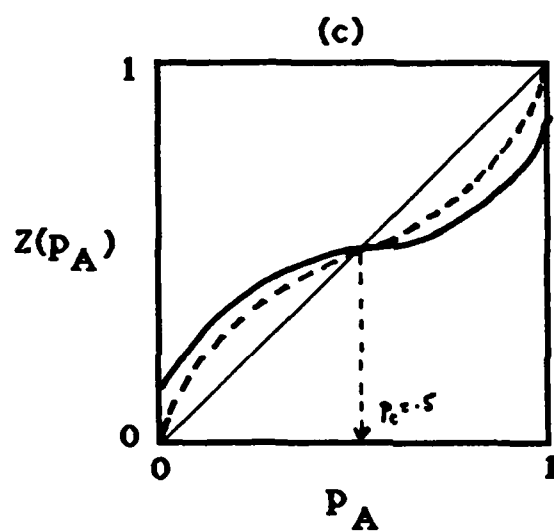
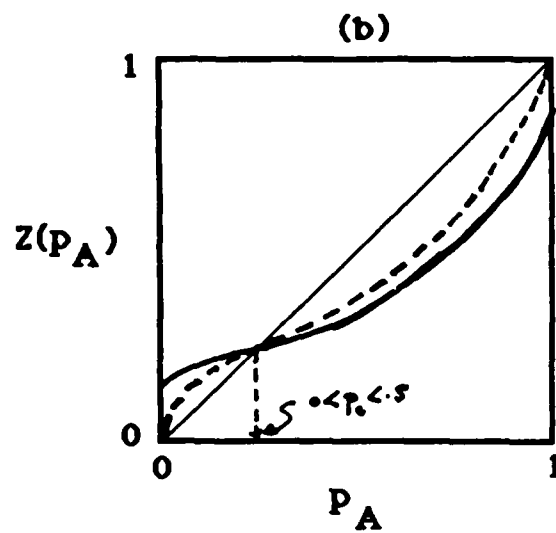
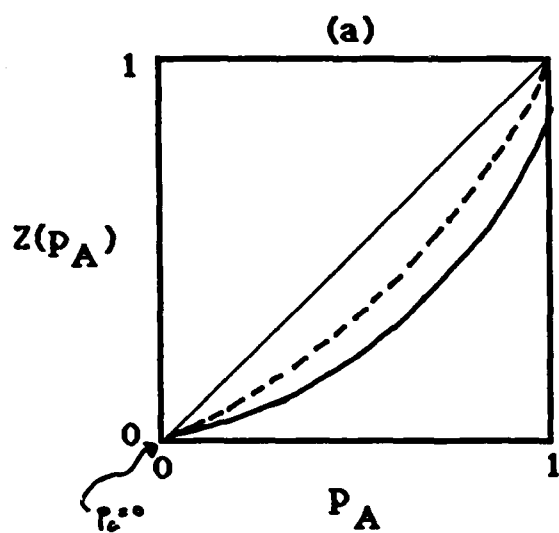
		C h o i c e s								
Probabilities:		.10			.50			.80		
Options:		Risky	Sure thing	Indif- ference	Risky	Sure thing	Indif- ference	Risky	Sure thing	Indif- ference
<u>Sure win</u>	\$2	62	25	9	57	24	15	38	34	24
	\$200	16	75	5	34	59	3	29	60	7
	\$20,000	5	88	3	16	77	3	26	66	4
		—	—	—	—	—	—	—	—	—
		83	188	17	105	160	21	93	160	35
		—	—	—	—	—	—	—	—	—
<u>Sure loss</u>	-\$2	38	48	10	59	21	16	58	10	27
	-\$200	48	39	9	41	40	15	52	31	13
	-\$20,000	47	41	8	39	42	14	49	30	17
		—	—	—	—	—	—	—	—	—
		133	128	27	139	103	45	159	71	57
		—	—	—	—	—	—	—	—	—

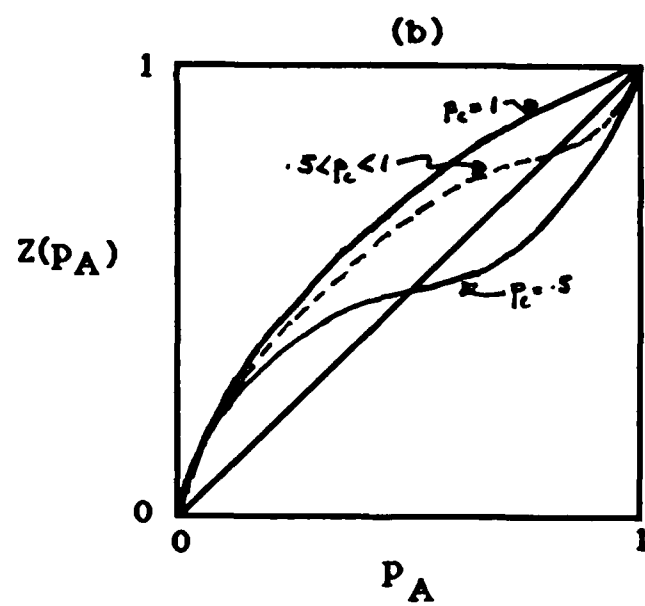
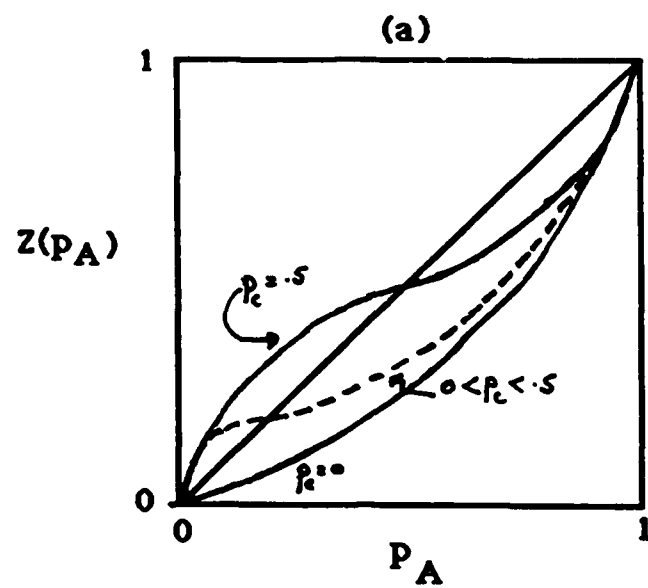
Cell entries are numbers of subjects choosing responses between a sure win (loss) and a gamble with equal expected value. Thus subjects were faced with choices (risky option, sure thing, or indifference) between, for example, \$2 and .10 chance at \$20, \$2 and a .50 chance of \$4, \$2 and a .80 chance of \$2.50, and so on.

Figure captions

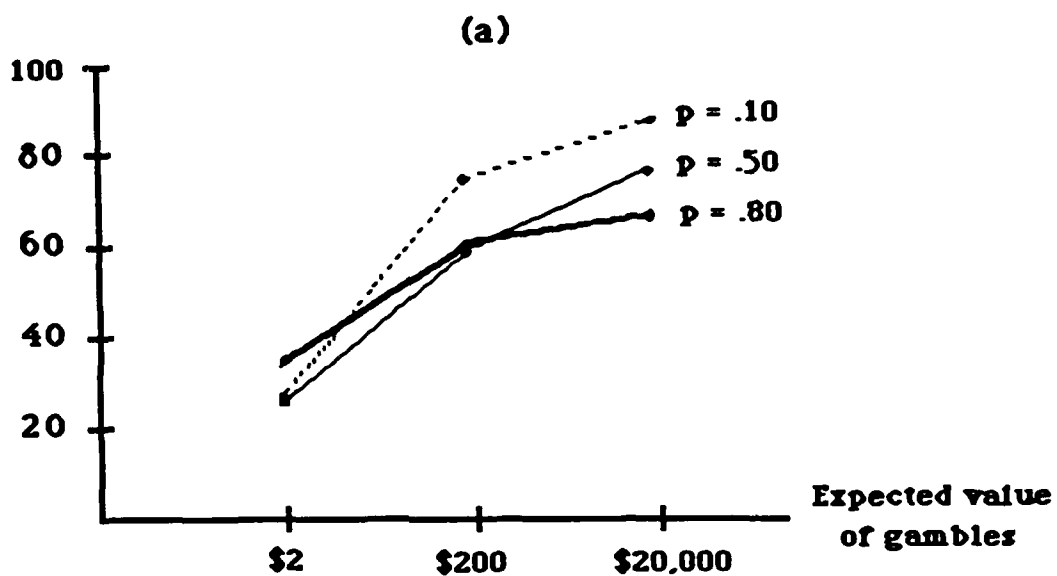
- Figure 1: Graphs of venture functions with variations in differential weighting given to values imagined above and below the anchor: (a) equal weighting, $p_C = .5$; (b) values below weighted more than those above, $p_C < .5$; and (c) values above weighted more than those below, $p_C > .5$.
- Figure 2: Graphs of venture functions showing effects of ambiguity (solid lines) compared to no ambiguity (dotted lines). These are drawn for the cases where: (a) $p_C = 0$; (b) $0 < p_C < .5$; (c) $p_C = .5$; (d) $.5 < p_C < 1$; and (e) $p_C = 1$.
- Figure 3: (a) Venture functions exhibiting qualitative differences between small ($p_C = .5$), intermediate ($0 < p_C < .5$), and large gains ($p_C = 0$).
(b) Venture functions exhibiting qualitative differences between small ($p_C = .5$), intermediate ($.5 < p_C < 1$), and large losses ($p_C = 1$).
- Figure 4: (a) Experiment 1: Numbers of subjects choosing sure thing at different probability levels -- Gains.
(b) Experiment 1: Numbers of subjects choosing sure thing at different probability levels -- Losses.
- Figure 5: (a) Experiment 2: Percentages of risk-averse subjects in different conditions.
(b) Experiment 2: Percentages of ambiguity-averse subjects in different conditions.



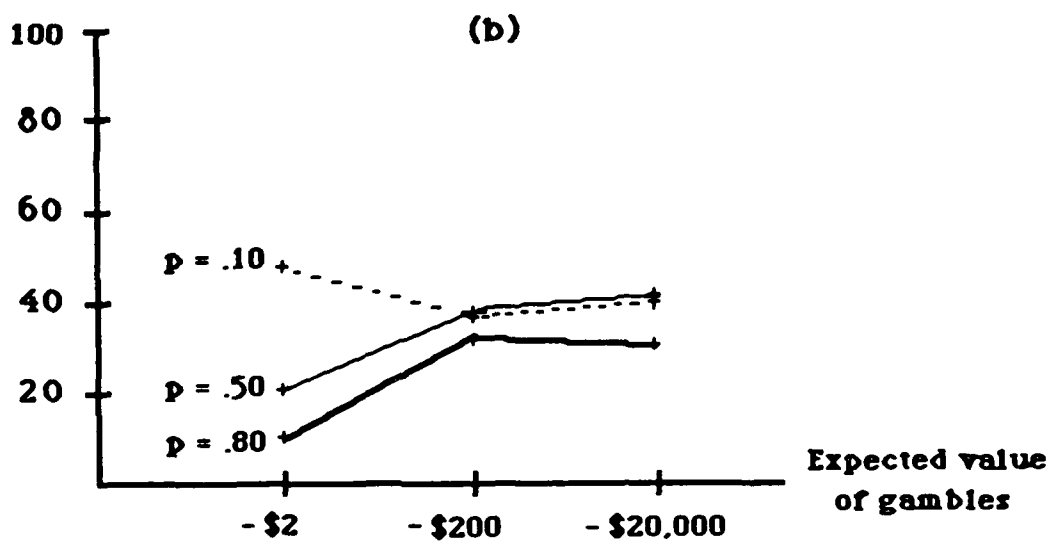




Number of
subjects
choosing
sure thing

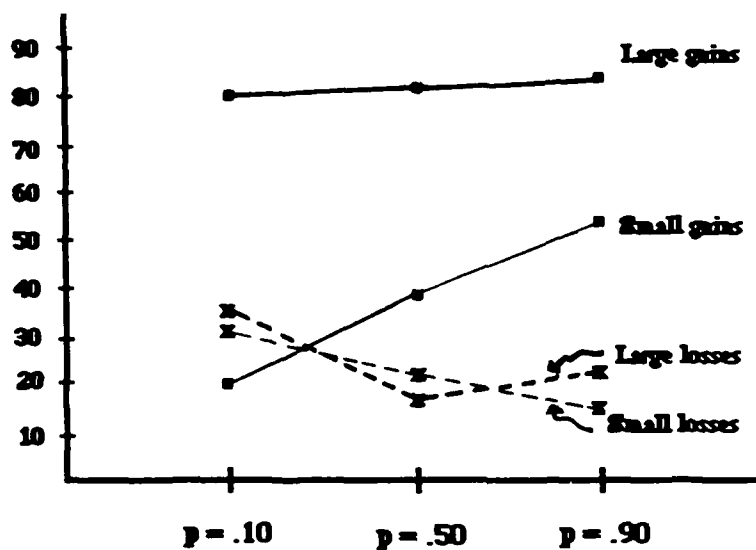


Number of
subjects
choosing
sure thing



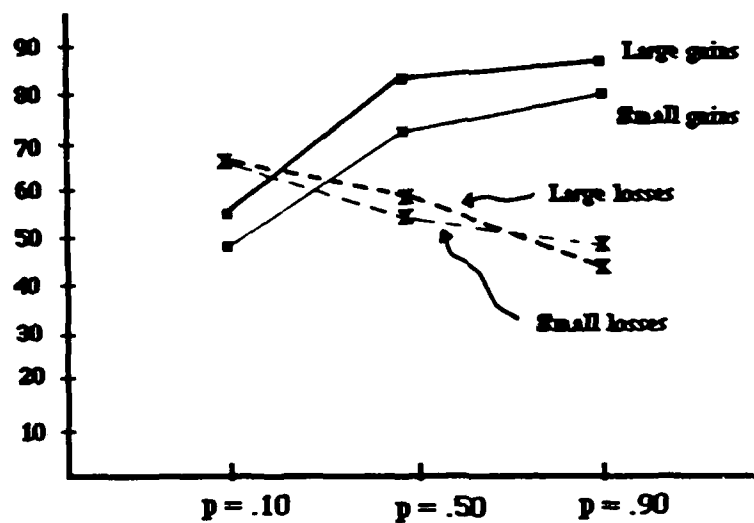
(a)

Percentage
Risk-averse



(b)

Percentage
Ambiguity-averse



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